(U) Robust Personnel Detection using PIR and Seismic Sensors

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Abstract

In this paper we analyze the signals from passive infrared (PIR) and seismic sensors to detect people. The PIR data analysis is done to determine the radiation source such as a human or an animal based on the signal strength, slopes of the signals, the number of Fresnel lens zones crossed by the target. The seismic data analysis is done to ascertain whether the footsteps belong to a human or an animal. If a mixed (both human and animal) signal is present, a single channel source separation technique will be used to separate them. The algorithms are tested on the data collected at the Southwest border.

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1. INTRODUCTION

Almost all the unattended ground sensors (UGS) used today for situational awareness consist [1] of a PIR and a seismic sensor in their suite of sensors. They are traditionally used as wakeup sensors, where they monitor the activity within their sensing area and wake up imaging sensors if they determine that a person or a target of interest is present.

Most of the PIR sensors are dual element pyroelectric sensors connected back-to-back as shown in Figure 1, to eliminate the background temperature variations. The sensor elements get charged when they receive the IR radiation from a target. The difference between the two elements will be amplified and the output will be available. In order to improve the energy collection capability of the sensor, we used a Fresnel lens array (model AA 0.53 GI V1) with five elements from Fresnel Technology Inc. Figure 2(a)

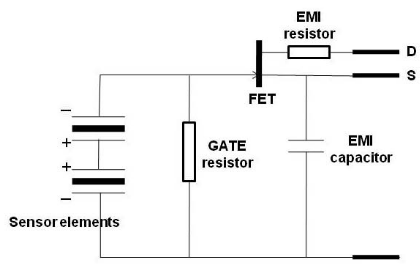
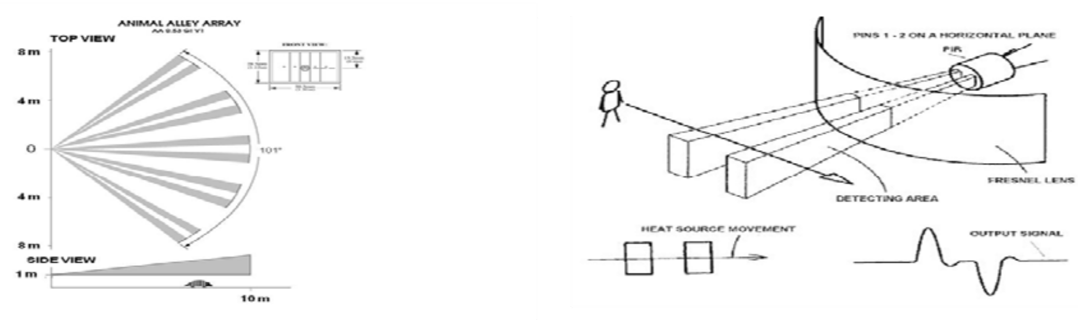


Figure 1: Schematic diagram of a dual element pyroelectric sensor

shows the Fresnel zone patterns of the array. The zone patterns are uniformly distributed along the 101° field of view. Basically, the angle between two zones is approximately 20°. Each zone is subdivided into two subzones due to the two-element structure of the sensor. Figure 2(b) show how the zones are created with the Fresnel lens array. Each zone of a subzone occupies approximately 3 - 5°. The Fresnel lens installed is an animal alley array. When the sensor is installed properly at a height of 1 m, there will be a dead zone of 1 m height where the sensor does not see. This is also evident from the side view shown in Figure 2(a).



(a) Zone patterns of the Fresnel lens array (b) Zone patterns of the sensor

Figure 2: Fresnel zone patterns and signal patterns

We analyze the signals generated by the PIR sensors (Figure 2(b)) to determine the length/width of a target to determine if the signal is generated by an animal or a person.

Next we analyze the seismic signatures generated by animals and people. To understand how different these signatures are, we look into the walking mechanism of humans and animals. As shown in Figure 3, when a person walks, the heel strikes the ground first and the front of the foot strikes next. Whereas, when an animal (quadruped) walks, its hoofs strike the ground like a hammer hitting the ground one at a time. Hence, the frequency spectrum for both targets will be quite different, and a proper set of basis vectors can be used to identify or extract the human and animal signatures.

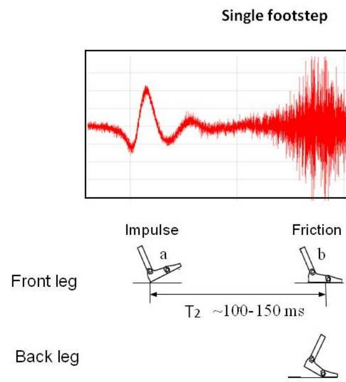


Figure 3: Mechanism for a person walking

In general, researchers concentrated on footstep signature detection [2] to establish the presence of humans. If a single person is walking, detecting cadence from the human footstep signature is relatively easy. However, when animals and people are walking in the vicinity of a seismic sensor, detection of a human foot signature is not as straightforward. If there are multiple sensors collecting the same signatures, one can use the principal component analysis (PCA) or independent component analysis (ICA) [3] to separate the human footstep signatures from animal footsteps depending on whether the noise is Gaussian or not. As mentioned earlier, UGS employed for personnel detection usually consists of only one sensor per modality, that is, one PIR, one acoustic, one seismic, etc., due to power restrictions. Therefore, it is not possible to use PCA/ICA for signal separation for most UGS. Hence, the presence of humans, animals, or both has to be inferred from a single seismic channel data. This is possible if the signals from humans and animals can be separated from a single seismic sensor's data. We use non-negative matrix factorization (NMF) techniques to separate the signatures.

In section 2, we present the information on how the PIR signature of a target varies with the type of target. Section 3 presents some of the single channel source separation to separate human and animal footstep seismic signatures. We also present results from the data collected at the field test conducted near the U.S. southwest border. In section 4, we present the conclusions and identify future directions.

2. PERSONNEL DETECTION USING PIR SENSOR

Detection of people and animals is done using two pyroelectric passive infrared sensors as shown in Figure 4. The sensors are placed one on top of the other. The beam pattern of the sensor at the bottom is horizontal to the ground, and the beam pattern of the top sensor is at a slope. As a result, the height at which the beams occur increases from one side to the other, as shown in Figure 4. Discrimination of humans and animals is done by estimating the width/length and height of each target, namely, humans and animals. The bottom sensor is used to estimate the width or length of the target, and the top sensor is used to estimate the height of the target.

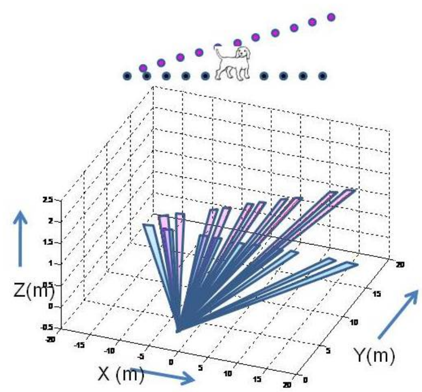


Figure 4: Target detection using two PIR sensors

Direction of motion of the target: From the bottom sensor output, one can easily estimate the direction of motion of the target. Since each beam pattern is assigned positive and negative signs, as shown in Figure 2b, depending on whether positive signal appears first followed by a negative signal or vice versa the direction of motion can be ascertained. If the sensor is installed such that the beam patterns are '+− +− · · · +−' from right to left with respect to the sensor, then a positive signal followed by a negative signal implies the target is moving from right to left. Similarly, a negative signal followed by a positive signal implies the target is moving from left to right with respect to the sensor. The same information can be ascertained using the top sensor's output as long as the sensor is able to receive the radiation from the target.

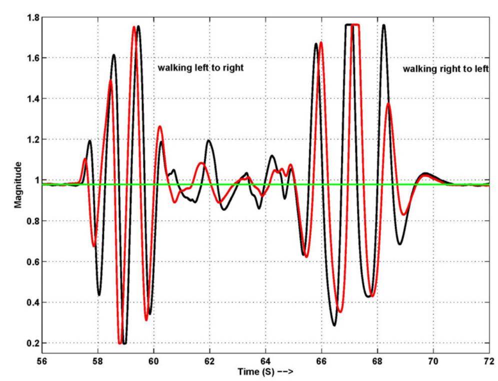


Figure 5: Signals generated by a person walking

Another way to determine the direction of motion of the target is to stagger (misalign) the beam patterns of the top PIR sensor with respect to the bottom sensor as shown in Figure 4. When a target walks from left to right, first signals appear on the bottom sensor and then on the top sensor since the target intercepts the beam pattern of the bottom sensor first and then the beam pattern of the top sensor. Similarly, if the target moves from right to left, then the signals appear first on the top sensor and then on the bottom sensor. Figure 5 shows the signals captured from bottom and the top sensor when a person walked across the sensor beams patterns left to right and right to left.

Data Collection: We performed a data collection exercise at a remote location near the southwest border of U.S. A number of scenarios were enacted, namely, (1) one person walking, two people walking, three people walking; (2) one horse walking, two horse walking, three horses walking; (3) one person and one horse walking, etc. The trail used for experimentation is shown in Figure 6. It also shows where the sensors are located on the trail. The signatures of a person and horse walking on the trail are shown in Figure 7. From Figure 7(a), when a person is walking, the signal variations are '- + - +' as the person crosses each beam, whereas when an animal is walking we find the variations are '- + + - + - - +'. The latter pattern can only happen when the width/length of the target is crossing two Fresnel zones at a time. This implies that the width of the target is at least two zones wide. If we know the separation between the

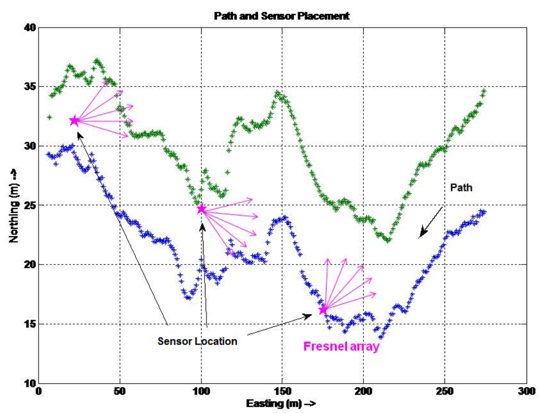
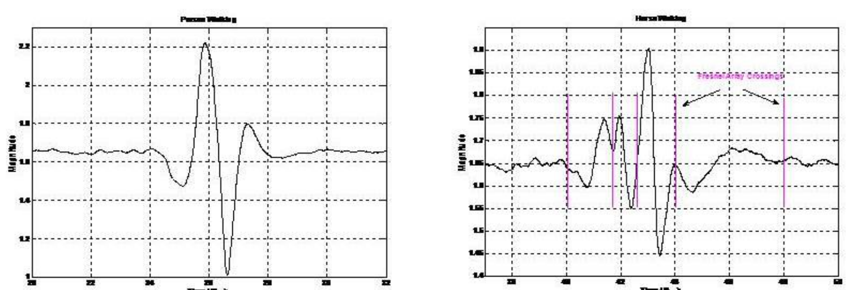


Figure 6: Trail used for collecting the data



(a) (b)

Figure 7: Signatures of a person and a horse walking on the trail

target and the sensor, we can estimate the widths of each Fresnel zone and compute the targets width/length, which in turn indicates whether it is a person or an animal. We also note from Figure 7(b) the time it took the animal to cross all the zones is greater than the time it took a person to cross them; another indicator that it is an animal.

3. PERSONNEL DETECTION USING SEISMIC SENSORS

In general, researchers concentrate on footstep signature detection to establish the presence of humans. If a single person is walking, detecting cadence from the human footstep signature is relatively easy. However, when animals and people are walking in the vicinity of a seismic sensor, detection of a human foot signature is not as straightforward. As mentioned earlier, UGS employed for personnel detection usually consists of only one seismic sensor, hence it is not possible to use PCA/ICA for signal separation. The presence of humans, animals, or both has to be inferred from a single seismic channel data. This is possible if the signals from humans and animals can be separated from a single seismic sensor's data. In acoustics, several researchers [4-9] have developed techniques for single channel source separation, where they attempted to separate signals from two speakers from a single microphone data. In almost all the cases, they used short-time Fourier transform (STFT) and non-negative matrix factorization (NMF) techniques [12]. We use discrete cosine transform (DCT) and NMF to separate human and animal footsteps in a single channel seismic sensor data. Next, we briefly describe NMF.

Let [*X*] be a [$t \times \omega$] matrix representing the STFT with $X_{t,\omega}$ denoting an individual element of [*X*] with variables in time *t* and frequency *ω*. NMF was first introduced by Lee and Seung [10-11], and was adopted by others to minimize the cost function

$$\frac{1}{2}\sum_{t,\omega}\left|\left|X_{t,\omega}\right|-\sum_{i=1}^{k}W_{t,i}\,H_{i,\omega}\right|^{2}+\lambda\sum_{t,i}\left|W_{t,i}\right|^{1};\quad \textit{such that } H,W\geq 0, \tag{1}$$

where $[W]_{t\times k}$ and $[H]_{k\times\omega}$ are the weight and basis matrices, and *λ* controls the sparcity on the weights and $|\bullet|^{1}$ denotes the L-1 norm. The number of basis vectors (*k*), which is also the rank of factorization, is usually chosen [10] so that $(\omega+t)k<\omega t$, and the product of *W* and *H* can be considered as the compressed form of the original data matrix [*X*]. The NMF technique [9] takes a given set of observed vectors (rows of [*X*]) and uses them to find a set of basis vectors (rows of [*H*]) such that any observation can be represented as a linear combination of these basis vectors. NMF selects the recurrent patterns in

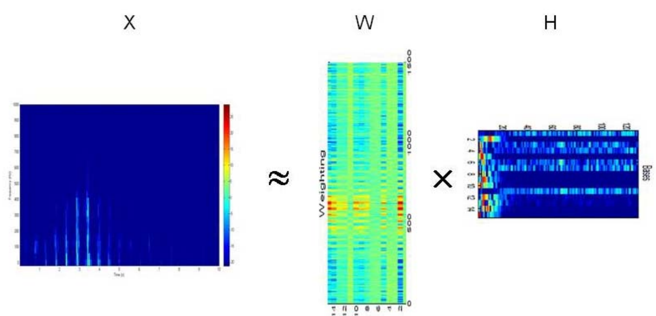


Figure 8: Factorization of a matrix

the observations as the basis vectors. Note that the rows of [*H*] are not orthogonal and can be thought of as overly determined basis vectors. Figure 8 shows a matrix factorization. NMF is distinguished from other matrix factorization methods in that all elements in the factorizing matrices must be non-negative. Non-negativity ensures that data are modeled as a purely additive combination of features; no cancellations can occur.

Figure 9 shows the seismic signatures of a person and a horse walking. It is evident that these signatures are impulsive and periodic. The period gives the cadence, which can be a discriminating factor if only one of the targets is walking at any time. Consider the case when both the targets are walking

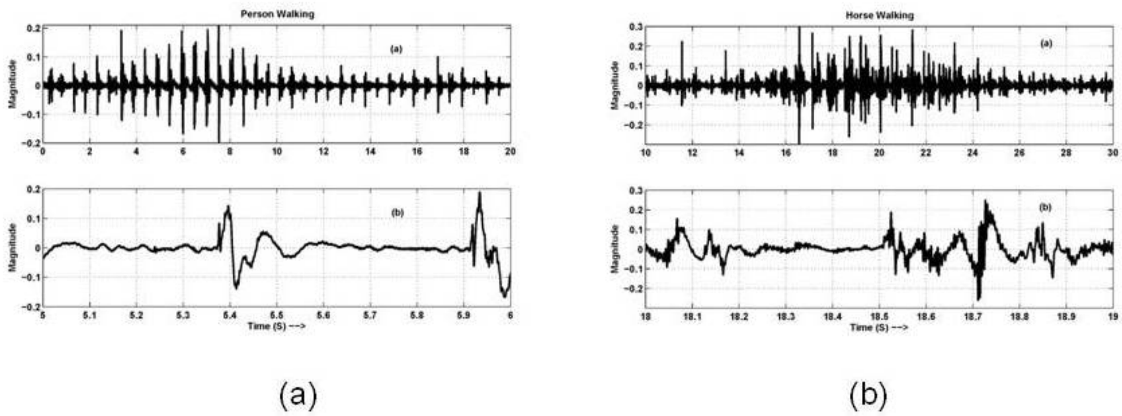


Figure 9: Seismic signatures of (a) a person walking, (b) a horse walking

simultaneously. Their joint signature is shown in Figure 10 and it shows that it is also impulsive in nature. The impulses may be periodic or not, depending on whether both the targets are walking in sync or not. Just by looking at the signature, it is hard to tell whether it belongs to a single human, a horse, or both. However, by separating the signatures of human and horse from it, we can determine if it contains a human or a horse, or both human and horse signatures. To do this, we need to build the basis vectors of human signatures and, similarly, we need to build the basis vectors of horse (animal) signatures.

Figure 10: Joint signatures of a horse followed by a man

In order to generate the basis vectors for both the targets, we select sample signatures of animals and people walking. We use discrete cosine transform (DCT) to convert each signature into frequency domain. The coefficients of DCT form the X matrix in equation 1. We use the NMF to generate the basis vectors H_p for seismic signatures of people and H_a signatures of animals. Since X matrix cannot have negative values, the positive DCT coefficients are denoted by X_p^+ and the magnitudes of the negative DCT coefficients are denoted by X_p^- such that $X_p = X_p^+ - X_p^-$. Their corresponding basis vectors are denoted by H_p^+ and H_p^-. Similarly, H_a^+ and H_a^- for the matrices X_a^+ and X_a^- corresponding to animals. In order to separate the signatures of people and animals, the following algorithm will be used.

Algorithm 1:

Step 1: Normalize the test signal *x*(*t*) after removing the mean. Compute X_t = dct (*x*(*t*)) and given by

$$X_t = X_t^+ - X_t^-$$

Step 2: Estimate the weights $\omega = \{\omega_1, \omega_2, \cdots, \omega_k\}$ and $\nu = \{\nu_1, \nu_2, \cdots, \nu_k\}$ such that

$$\left|X_t^+ - \omega H^+\right|^2 + \left|X_t^- - \nu H^-\right|^2;\ 0 \le \omega_i, \nu_i \le u_b; \quad \forall\, i \in \{1,2,\cdots,k\}$$

is minimum, u_b is typically 1 and

$$H^+ = \begin{bmatrix} H_p^+ \\ H_a^+ \end{bmatrix}; \quad H^- = \begin{bmatrix} H_p^- \\ H_a^- \end{bmatrix}.$$

One may use any constrained nonlinear optimization program, such as the "*fmincon*" function in MATLAB [13], to perform this task. "*fmincon*" employs the interior-point algorithm. The interior-point approach to constrained minimization is used to solve a sequence of approximate minimization problems.

Step 3: Non-zero weights ω and ν give the bases used to represent X_t.

Step 4: Reconstruct the signal $\widehat{X}_t$ by taking the inverse DCT (IDCT) of the difference $\left(\omega H^+ - \nu H^-\right)$.

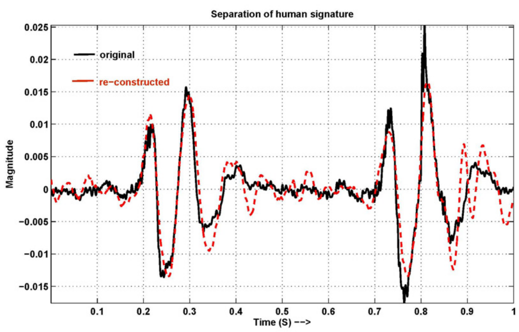
Step 5: Signature corresponding to a person is given by

$$IDCT\left(\left(\omega_1 \cdots \omega_r\right)H_p^+ - \left(\nu_1 \cdots \nu_r\right)H_p^-\right),$$

and signature of the animal is given by

$$IDCT\left(\left(\omega_{r+1} \cdots \omega_k\right)H_a^+ - \left(\nu_{r+1} \cdots \nu_k\right)H_a^-\right).$$

We took two signatures; one from each target and mixed them to generate X_t, then we used the above algorithm to separate two signatures. The results are shown in Figures 11 and 12. Clearly, it is seen from these figures that the separation of signatures is achieved. Compared to a human signature, extraction of the horse signature is not as one would expect. The reason is that there are a large number of high



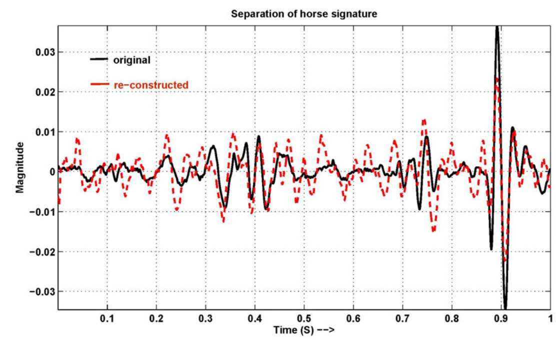


Figure 11: Original & re-constructed Signature of a person

Figure 12: Original & reconstructed signature of a horse

frequency components in the database of the horse signature and the number of basis vectors might not have been sufficient. However, the essential parts (impulse) of the horse signature are reconstructed well. Since the weights of the basis vectors determine whether the signature belongs to a horse or a person, their sum can be used to determine for detection of the presence of the target. Let

$$S_p = \sum_{i=1}^{r} (\omega_i + \nu_i); \quad S_a = \sum_{i=r+1}^{k} (\omega_i + \nu_i),$$

then we determine the presence of a signature of a person if $s_p > s_a$ or the presence of the signature of an animal if $s_a > s_p$ or if $s_p \approx s_a$ and they are above certain threshold, then we declare that the

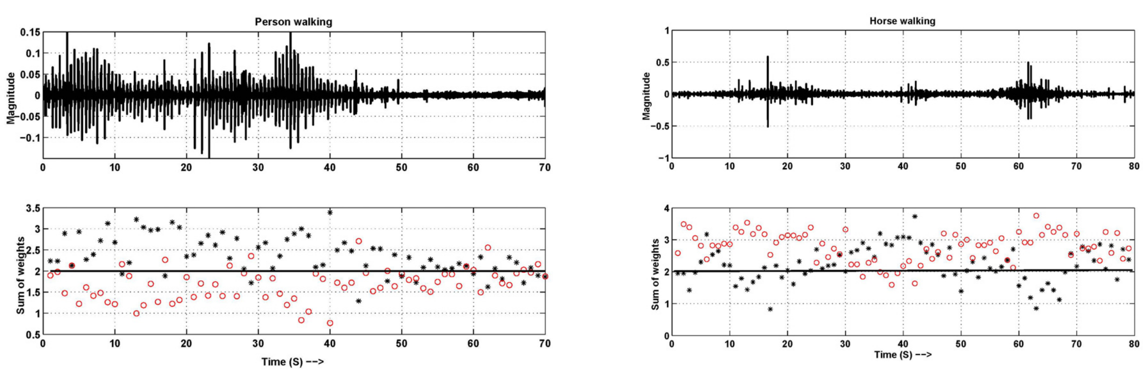


Figure 13: (a) Detection of a person, (b) detection of an animal

signatures of both the targets are present. Figure 13 presents the results when (a) a person and (b) an animal was walking.

4. CONCLUSION

In this paper, we presented the problem of personnel detection using PIR and seismic sensors. In the case of a PIR sensor, the detection is done based on the length/width and height of the target. The length/width and heights are estimated using the number of Fresnel zones occupied by the target simultaneously. In the case of seismic sensor, we showed a method how to separate the seismic signature of animals and people. The sum of the weights corresponding to the basis vectors of each target gives the detection criteria for those targets.

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